Energy consumption prediction for heavy electric vehicles based on the operating cycle format

Master's thesis in Systems, control and mechatronics

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Abstract

The objective of this report is to study the energy consumption of a heavy electric vehicle while it is on the road driving along an unknown route. The results from this project deliver a method and a framework that can be used to estimate certain environmental factors' energy consumption affect on a vehicle. The focus lies on investigating factors that can be hard to predict, or which there is no information about before embarking on a route. The energy consumption from all factors' is summed up to give a final estimation. A connection between the different factors characteristics and the energy consumption is established by running simulated scenarios generated by stochastic models of the investigated factors.

The findings of the project are the relations between characteristics of the factors to its energy consumption. When the variance of the topography increases, an increase in the energy consumption can be observed as well. This observation demonstrates the relation between the characteristics with their corresponding influence on energy consumption. Similar conclusions can also be observed for the two other investigated parameters, curvature and speed bumps. The results are based on the assumption that summing the energy contributions from each factors model gives a total energy consumption for the vehicle along a route. The results of the project show that it is possible to estimate the energy consumption for other parameters with similar physical properties as well. This is especially important for parameters which are hard to calculate before starting a route. The findings consists of a series of constructed graphs that represents the simulations. These graphs contain information to map a set of an interval of investigated characteristics such as the variance values, mean curvature and speed bumps intensity to an energy consumption estimate.

Keywords: energy consumption, operating cycle, heavy electric vehicle, prediction, stochastic model, unknown route.

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Marcus Berg, Conny Ta, Gothenburg, Januari 2022

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

dOC	Deterministic Operating Cycle
EV	Electric Vehicle
HEV	Heavy Electric Vehicle
ICE	Internal Combustion Engine
OC	Operating Cycle
sOC	Stochastic Operating Cycle
SoC	State of Charge
SoH	State of Health
VECTO	Vehicle Energy Consumption calculation tool
VehProp	Vehicle Simulation Environment

Nomenclature

SYMBOL	EXPLANATION
E	Energy consumption
E_{tot}	Total energy consumption
E_0	Base energy consumption
E_Z	Topography energy consumption
E_C	Curvature energy consumption
E_B	Speed bump energy consumption
λ	Intensity of an event
Topography	
L	Total length (mission distance)
L_s	Segment length
y, Y	Road grade
a	Topography autoregression coefficient
e	Noise term
$\mathcal{N}$	Normal distribution
σ_e	Amplitude error
σ_Y	Standard deviation
σ_Y^2	Variance
z	Altitude
Curvature	
x, X	Location
Exp	Exponential distribution
L_c	Curve length
C	Curvature
λ_C	Curve intensity
R'	Shifted road radius
r_{turn}	Minimum road radius
σ_C	Curve radius variance
μ_C	Log-normal mean of (shifted) radius
λ_C	Curve intensity
μ_L	Expectation value of curve length
σ_L	Standard deviation of curve length

Speed bump

S_h	Speed bump height
S_l	Speed bump length
S_α	Speed bump angle
v_{min}	Minimum velocity
v_{max}	Maximum velocity
v	Vehicle speed
λ_b	Speed bump intensity

Characteristics estimation

$M, \bar{X}$	Mean value
α	Forgetting factor
λ_b	Speed bump intensity
T	Storing term
W	Weight factor
S^2	Variance

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1
Introduction

Research within the area of range estimation for road vehicles is becoming progressively important with the shift in the automotive industry towards electrically-propelled vehicles. For electric vehicles, the range concern is of major importance due to the limitations derived from the energy capacity of the batteries.

This thesis aims to use and expand upon the already existing operating cycle (OC) format developed by the COVER project to better understand the effect environmental factors have on the energy consumption of a vehicle [3]. To do so, the project aims to create a framework for finding the correlation between the collected incoming data for different environmental factors and the required energy consumption of the vehicle while on the road. This will allow a prediction of the total energy consumption.

1.1 Background

Electric vehicles (EVs) take time to charge and combined with the lack of good infrastructure for charging stations [4] this may cause the careful driver to account for greater planning of the route than what would be necessary for an internal combustion engine (ICE) propelled vehicle. If better range estimations could be made for routes where the environmental conditions ahead are unknown, the efficiency of vehicle operations could potentially increase. Estimating the energy consumption for the unknown routes with unknown environmental conditions ahead is what this project tries to accomplish.

There are some advantages for EVs over traditional ICE vehicles, two examples being, good energy efficiency and reduced noise pollution [5]. However, the possible driving range of EVs is not yet close to that of ICE vehicles even though significant advances in battery technology have been made. These include a higher energy capacity and lower production costs [4]. The range capacity of EVs varies depending on the battery but some sources found that it may be as low as 22% of the range of what the conventional ICE vehicle would be able to reach [5]. Because of the uncertainty that comes with limited range, researchers have observed what is called "range anxiety" associated with EVs. It has been observed that most drivers currently reserve at least 30% of the total possible remaining range due to the uncertainty of trusting the range estimation for the EV to be accurate [5]. This is not ideal from an efficiency standpoint. By introducing more accurate predictions for the range estimation, the driver of the vehicle could feel more confident that it can be used closer to its actual limit without worrying about running out of battery.

In this project, the range estimation is defined as the prediction of the range in km that can be achieved based on the current remaining charge of the EVs battery. Having a more accurate prediction should, as stated earlier, help with route planning and decision making to more efficiently plan transport missions. For this project, the focus will be on heavy electric vehicles (HEVs) or more specifically electric trucks. To estimate the range of the HEVs the total energy consumption used throughout a route has to be estimated first.

The traditional way of estimating the energy consumption for a vehicle is by using a conventional driving cycle. A conventional driving cycle is generated by placing and driving a vehicle on rolls (chassis dynamometer) [6]. The results are then monitored for different speeds over some time and the energy consumption for a certain speed can then be extracted.

For heavy-duty trucks the approach is somewhat different, where instead of the vehicle being placed on a chassis dynamometer, it is tested by using the numerical simulation software VECTO. The software contains properties such as the road gradient, auxiliary power requests and also a set target speed. It is a more complex approach where five different driving cycles are used, each for a different specific type of environmental condition such as; long haul, urban, delivery, construction, etc. This approach is instead referred to as a target speed cycle [1].

1.2 Clarification of terms and concepts

Before delving into the theory there are a couple of key expressions and concepts which needs to be clarified.

Environmental factors that affect the vehicle such as the topography, curvature or speed bumps, are simply referred to as parameters. These parameters are extensively covered in the report by Pettersson [1]. These parameters are subdivided within the categories road, weather, traffic and mission, as can be seen in figure 1.1, together they make up the driving cycle format called the operating cycle (OC) format. Both the conventional driving cycle format and the target speed cycle format lacks many of the parameters included within the OC format. The OC format allows for a better representation of the real-world behavior and was proposed by the results from the COVER project [3].

Every parameter can be described by several characteristics. To give some examples. For topography, it could be the variance of the slope along a route. For speed bumps, it could be the intensity of the speed bump frequency. Both the variance and intensity are in these cases examples of what parameter characteristics are.

The operating cycle used in this project encompasses a set distance of 152573 m. When driving the entire distance, this is referred to as driving a "full operating cycle". This distance was set because of it being a case used in [2]. The OC is used in VehProp, which is an environment including a vehicle model and how it is exposed to its surroundings developed by the COVER group. The remaining parameters apart from the ones of interest, such as those included in the weather and traffic categories of the OC format, do not matter for the results of this project since they are set to have no influence. Another key concept is how the energy consumption for the vehicle is defined in this project. It is defined as the energy demand from the HEVs battery. The word energy consumption is related to the total energy drained, subtracted with the regenerated energy, throughout the whole OC.

Another important concept is that of transport operations. In the report "Operating cycle descriptions for road vehicles" Pettersson describes transport operations as "An enumerable number of tasks along a specific route", meaning it describes the tasks the vehicle performs along a route [1]. Pettersson goes on to specify that the transport operation tasks can be further broken down into certain categories such as the traffic, weather or road categories.[1].

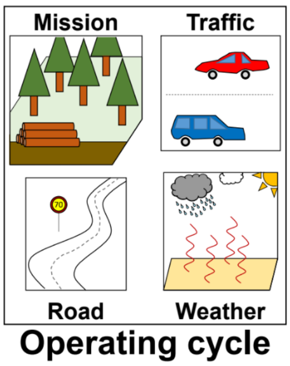

Figure 1.1: Graphically view of the operating cycle format [1]

The four categories mentioned also have further subcategories where for example, the road can be divided into further parameters, as seen in figure 1.2.

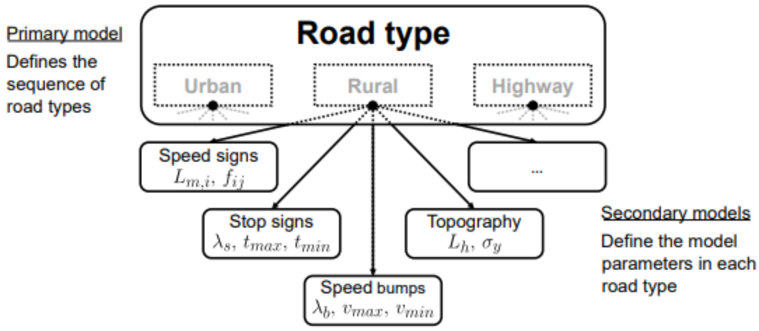

Figure 1.2: Example of the road category division [1]

This approach tries to step away from the target speed cycles and instead create statistical models generating a complete simulation environment. The approach strives to make a more accurate simulation of the real-world behaviour of the vehicle performance.

1.2.1 Previous work within range estimation

The literature regarding range estimation for EVs is quite extensive but most of it does not include one or more significant factors that are impacting the range. The factors can for example be auxiliaries power requests, weather, traffic or road conditions [4]. Below, a summary is given of the relevant literature found within the area of range estimation when conducting a literature search at the start of the project.

In the report "A Data-Driven Method for Energy Consumption Prediction and Energy-Efficient Routing of Electric Vehicles in Real-World Conditions" [7], the goal is to reduce range anxiety by presenting an energy consumption estimation method for EVs. The report also uses the idea of looking at real-time environmental parameters affecting the vehicle, such as weather and road properties. The authors then combine this with collected data and connect it for several road segments, based on the similarity between the incoming and the already collected data. To establish an energy consumption estimate for each of the road segments, a linear regression method is used. The linear regression model is given data from a neural network that estimates the "unknown microscopic driving parameters over a segment before departure, given the road segment characteristics and weather conditions". The results from the report state that it predicts the true energy consumption with a mean absolute error of 12-14%.

However, this approach assumes that a road network is mapped before departure to train the neural network. This is done to find the most efficient route.

Another approach is proposed in the report "A multi-mode electric vehicle range estimator based on driving pattern recognition" [8]. To predict the speed or driving profile of the vehicle, the suggested approach is to beforehand calculate the energy consumption for different driving features or patterns and thereafter categorise them into different so-called clusters. The vehicle will in real-time use the data measured throughout the trip and categorise it into one of these clusters to predict the energy consumption in the following short time horizon. The proposed energy consumption estimation gave a 9% average error when validated against real data. The approach of the report allows the method to be implemented in a time-efficient manner but the drawbacks are that it does not include weather, auxiliaries power requests, road or traffic individually. The parameters are instead baked into the measurements and models.

Yet another approach was proposed in the report "Accurate Remaining Range Estimation for Electric Vehicles" [5]. The approach focuses on the vehicles model which includes external loads, a battery model and regenerative brakes. The drawback of the report is that it neglects the aerodynamics due to the low velocity used in the experiments and also ignores the traffic. These two factors have a huge impact on a more realistic scenario. The authors claim an accuracy error of the energy consumption to be around 2.5% and pointed out there were two factors that mainly contributed to that. These were the copper loss in the traction motor and the non-linearity of the power consumption that did not get implemented in the model. The result is good but lacks many parameters which have a high impact on energy consumption.

1.3 Aim

The aim of the project is to create a framework to map the characteristics of parameters to the energy consumption for heavy electric vehicles. The goal is to predict the total energy consumption with the use of mapping. This will be done while the vehicle is on the road for an unknown route, meaning only measured data collected during the trip is used to predict the total energy consumption. The framework will use the operating cycle format proposed by the COVER/OCEAN project which is based on a statistical approach. This format is explained in further detail in the coming chapters.

1.4 Limitations

- Construction of new models for different parameters is not required since many of the most important models already exist in VehProp.
- The prediction for the energy consumption will only focus on an unknown route.
- The project will only focus on heavy electric vehicles, HEV, but road properties are still somewhat independent of the vehicles. This can be used for other vehicles as well even though parameters such as the slope has a much greater impact on heavy vehicles than smaller vehicles such as a car due to the difference in weight/output ratio.
- Implementation of the approach will be done in the MATLAB environment.
- Tests on the approach will only be focusing on data-based stochastic models, sOC. Testing out in the field is outside of the scope of the project.
- The driver naturally has a huge influence on energy consumption. In this project, the behavior of the driver has not been considered and instead a standard driver model is used.

1.4.1 Simplification

To produce the desired results of the project in a time feasible manner, some simplifications have been made for the extensiveness and representation of the parameter models used. As discussed previously, reaching the goal of accurately predicting the vehicles energy consumption requires as many parameters as possible that affect the vehicle to be included, such as; wind, road topography, road curvature, speed bumps, stop signs etc. To narrow the project's scope a decision was made to focus on certain key parameters which have a greater impact on energy consumption and that was best in line with the proposed ideas for how to tackle the problem differently. These parameters ended up being the topography, curvature and speed bumps.

In theory this means that parameter models which might have a great impact on the total energy consumption but are generally hard to model will not be included. Such as, the drivers driving pattern, road construction, special events obstructing traffic or battery ageing just to name a few.

1.4.2 Verification

Many literature sources use real vehicles to verify their results, which is a good approach but it is a rather time-consuming approach and outside the scope of this project. However, verification with simulation data has the benefit to test thousands of scenarios straightforwardly. The drawback is that there will be some errors inherited from the simulations. The simulation will naturally not replicate real-world values as good as the real vehicle already does, therefore, it becomes a trade-off question in terms of accuracy versus time efficiency.

In this project, there will only be verification on the powertrain and not on the approach itself due to the time constraint. The effects will be examined when the mass of the HEV is doubled. Although, there will be a suggestion on how to verify the results of the mapping system between the parameters' energy consumption and the parameters' characteristics.

1.5 Specification of the issue under investigation

- How can the models in the OC format be used to make an energy consumption prediction for heavy electric vehicles in cases of unknown routes?
- How do different environmental factors affect the energy consumption of the vehicle?

1.6 Ethical and sustainability aspects

Using fossil fuels releases lots of greenhouse gases and other emissions and contributes to global warming. The road transportation sector contributes a big chunk of the total emissions in the world. For example, Europe releases around 10% of the total global emissions where about 25% of that comes from the transport sector [1]. Using electric vehicles could be a replacement for conventional gasoline vehicles as electric vehicles have shown promising results in terms of growth in the sector [9]. This is however just a replacement and does not solve the problem entirely which would be the best case, but is difficult in our fossil fuel reliant society. One of the UN goals for sustainable development is to use more clean energy, and if heavy electric vehicles become more popular and reliant in terms of range predictions, then the goal is being worked towards. Also, as noted earlier, a more accurate way to predict the range for heavy electric vehicles would lead to fewer charging sessions therefore also benefiting the environment.

There is also the aspect of range anxiety which is discussed in several relevant reports about range estimation [4], [5]. The uncertainty of trusting the accuracy of the estimation of the vehicle combined with the limited infrastructure for charging can cause range anxiety for EV drivers. This can hopefully be relieved by a more accurate prediction of the range.

1.7 Thesis outline

Chapter 2 describes the operating cycle format and how an energy consumption prediction is made when the history of the road is not known. In chapter 3, selected environmental factors are described and also how to estimate the characteristics of the factors. How the electric powertrain was modified and how it works is explained in chapter 4. The results, simulations and verification are examined in chapter 5.

In chapter 6 a discussion was had and conclusions were drawn from the results. Chapter 6 also give suggestions on what the future work should focus on based on the results from this project.

2
Operating Cycle

This chapter will go further into what the OC format is, its structure and how it is used. The chapter will also discuss the theory behind reaching the goal of this project. It will therefore discuss how the connection between some selected environmental factors affecting the vehicle and the energy consumption associated with them was established.

2.1 Operating cycle format

As previously discussed, the purpose of the OC format is to take into account the surroundings of the vehicle to provide an accurate estimation of its behaviour within it. All definitions and concepts discussed within this section comes from Pettersson's report [1], and should therefore be referred to for a deeper insight.

The format is separated into high-, mid-and low-level descriptions which are called the classification, variation and simulation descriptions. The distinction between them is the level of detail they describe for the transport operation and can be used for different purposes.

A transport operation is by Pettersson defined as "an enumerable number of tasks along a specific route". The transport operation can be broken down into the four categories discussed earlier, namely the road, weather, traffic and the driver actions. If data can be collected for all of the transport operations according to the definition above, one would then be able to construct what Pettersson calls a "transport application", which describes a vehicle use case.

2.1.1 Operating cycle classification

The classification description. A high-level description of the vehicle surroundings is used to determine the similarities and differences of the transport applications rather than describing them in detail. Another reason for the high-level description is to give information about what parts for the vehicle best suit the transportation applications it is used for.

The variation description. To only have information about the high-level description is not enough to determine the whole transport application, since it simply does not include any variations. The variations will give the characteristic of the operating cycle which in turn gives more details to label it under one of the high-level descriptions.

To describe an OC format, there are a lot of parameters needed. Three of these that will be covered in this project are the topography, curvature and speed bumps. The parameters need to be defined in a statistical way to fit the variation description. Parameters are arranged in a hierarchical structure and are called stochastic operating cycles, sOCs.

The simulation description. Going even deeper into detail, the next description is a low-level description. At this level, the OC should reflect the real world in form of data for simulations.

Equivalent to the sOC, the simulation description will include data that the sOC generates. This format is called a deterministic operating cycle, dOC, format.

2.1.2 Stochastic operating cycle (sOC)

The sOC format encompasses as the name suggests stochastic models for the chosen parameters where dOCs are generated from. The models for the investigated parameters are given in detail in chapter 3. The parameter models differ in type depending on the parameter. A summary of the properties for the road can be found in figure 2.1.

Road property	**Model type**	**No. of states**	**No. of parameters**
Road type	Markov process	n_r	n_r^2
Stop signs	Marked Poisson	Continuous	3
Give way signs	Marked Poisson	Continuous	5
Traffic lights	Marked Poisson	Continuous	5
Speed bumps	Marked Poisson	Continuous	3
Speed signs	Markov process	n_s	n_s^2
Ground type	Markov process	n_g	$n_g(n_g+1)$
Topography	Gaussian AR(1)	Continuous	2
Curviness	Marked Poisson	Continuous	6
Road roughness	Laplace AR(1)	Continuous	2

Figure 2.1: Overview of the parameter models for the road in the sOC format [1]

2.1.3 Deterministic operating cycle (dOC)

The dOC format contains the information finally used as the input for the powertrain model described in chapter 4. This input is represented as a data set where the first data set is the longitudinal position and the following data set varies depending on what parameter is being investigated. For example, the topography has its altitude as the following data set. The structure of the dOC format for topography is illustrated in figure 2.2.

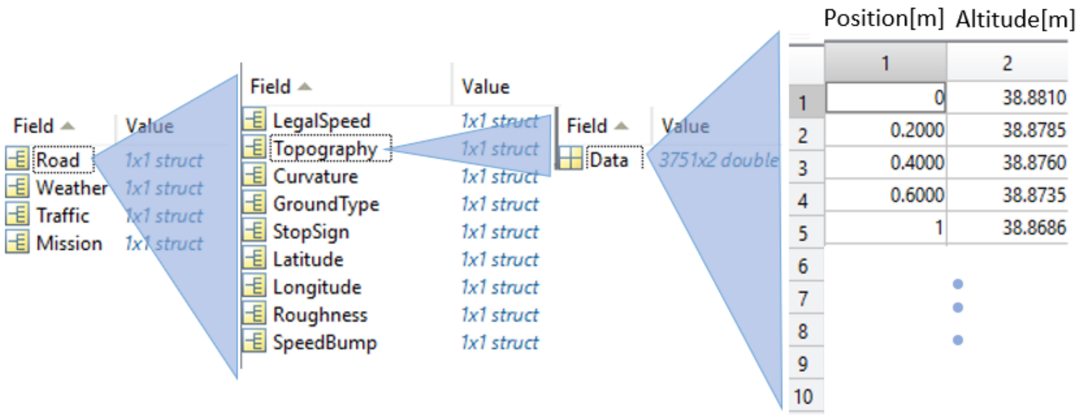

Figure 2.2: Overview of the dOC format structure in the Matlab environment and parameters of the road category.

2.1.4 Operating cycle connection

For each parameter, there are one or multiple characteristics of the parameter defining how the data set will be generated. Choosing values in an interval for each one of the characteristics gives multiple sOCs. Each sOC can in turn generate a bunch of random dOCs, which contains a data set of what the parameter looks like, such as altitude for topography. The dOCs varies depending on what values have been chosen for the characteristics of the parameter. See figure 2.3 for an illustration of such a connection.

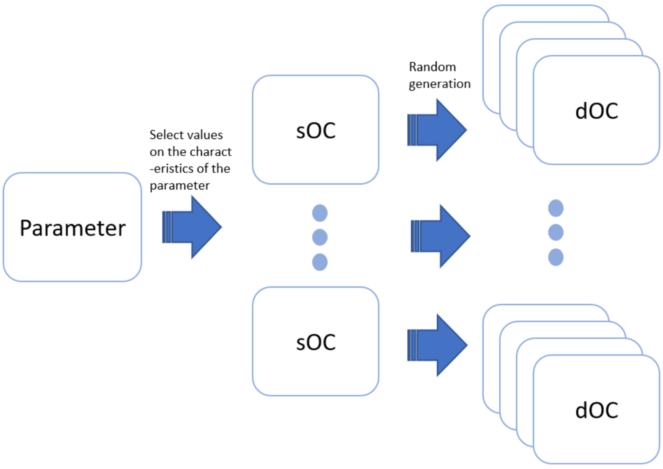

Figure 2.3: By choosing parameter characteristics values in an interval, each characteristic gives multiple sOCs which in turn can be used to generate a bunch of random dOCs.

2.2 Energy consumption estimation for the unknown route

For the vehicle travelling along the unknown route, future predictions will be made based on data measured actively during the mission. This could in practice be that while the HEV is travelling on the road, a prediction of the total energy consumption will be made. There is also a case where the route is known, which instead relies on historical and available data throughout a mission to determine the total energy consumption. This is what the so-called offline case is about, which is what the COVER project has focused on previously. For the online case, it is not however strict that only predictions of the parameter characteristics should be made at the current moment. For this case, some historical data can be used as an estimation. This means that the online case could include both known and unknown routes which could provide a more accurate solution. To start off, the focus will only be on the approach for estimating the energy consumption for the case of unknown route. This will include where the approach came from, how it works and how it is created.

2.2.1 Inspiration

In the report [8], the authors identified the different driving patterns and categorised them into different data clusters, this was described in section 1.2.1 but their method of how it was done will be described even deeper here. Each of the clusters represents a unique set of characteristics. This was done preemptively and in a real-world setting with real vehicles. The driving patterns were based on several set thresholds, for example, if the velocity for a certain segment of the road reached above or below the set threshold then the driving pattern for that segment was labelled as fast, slow, hilly, flat or other labels. This way, the label could then at a later point for a "live-case" scenario be mapped to a particular cluster based on the observed characteristics. This cluster can then be mapped into the corresponding energy consumption prediction.

Instead of using raw data and checking if it reaches above or below certain thresholds and sorting into different clusters, this project aims to take a somewhat different approach. The approach is to estimate the characteristics of the data and then map them to pre-calculated energy consumption. The variance of altitude, as mentioned earlier, is one example of such a characteristic for the topography. The benefit of this is that it gives more general information combined with a better overview of the whole data set.

2.2.2 Creating the mapping system

A mapping system needs to be created to map the parameter characteristics to pre-calculated energy consumption estimates. This is done by, as briefly mentioned earlier, selecting some values in an interval for each parameter characteristic and then generating a bunch of dOCs, see figure 2.4. When multiple characteristics of one parameter are being used, the mapping will be a multi-dimensional graph. For each dOC, energy consumption can be extracted. For each bunch of the dOCs, a mean value is then calculated to represent the general energy consumption for the specific value of the parameter characteristic. An overview of how it would work if just one characteristic were considered is illustrated in figure 2.4.

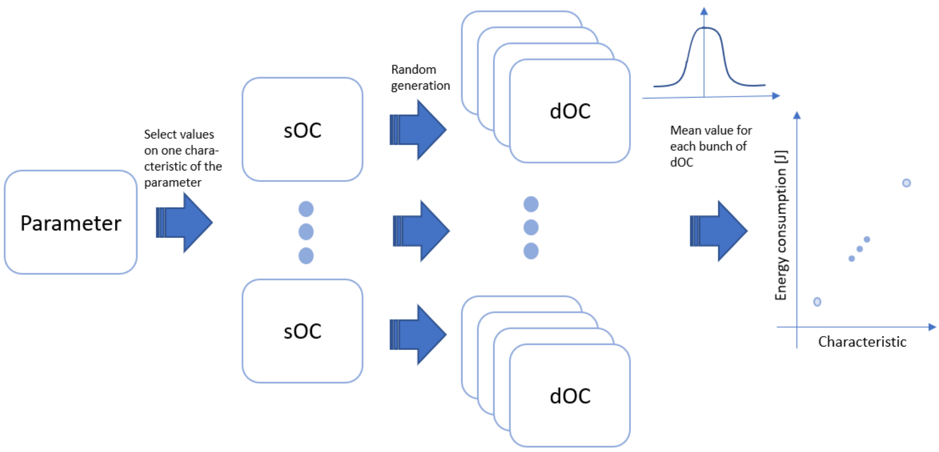

Figure 2.4: Choosing values in a interval for one parameter characteristic gives multiple sOCs which in turn can be used to generate a bunch of random dOCs. The mapping system can then be created with the mean values for each dOC bunch and the values of the parameter characteristic

2.2.3 Computational effort of simulating Operating Cycles

The number of dOCs generated for each parameter is chosen to be 100 since this number of dOCs gives a sufficient linear relation between the parameter characteristics and its energy consumption. Using instead a higher number, such as 1000 dOCs, will increase the computational effort exponentially. Based on the preliminary trials, the higher number of dOCs seems to give similar results as 100 dOCs. The decision was therefore made that 100 dOCs are sufficient enough for achieving the desired outcome.

2.2.4 Application to the live situation

What would the results of the project finally lead to? It is assumed that there is already a way to measure the data needed for the parameters when travelling the road. The next step will be to estimate the parameter characteristics and then mapping those to the correlated energy consumption that has been pre-calculated, see figure 2.5 for the method. All the different parameters of energy consumption will then be summed up. Each time new data comes in, a new estimation will be done for the parameter characteristics and a new energy consumption estimate for the parameters will be summed up.

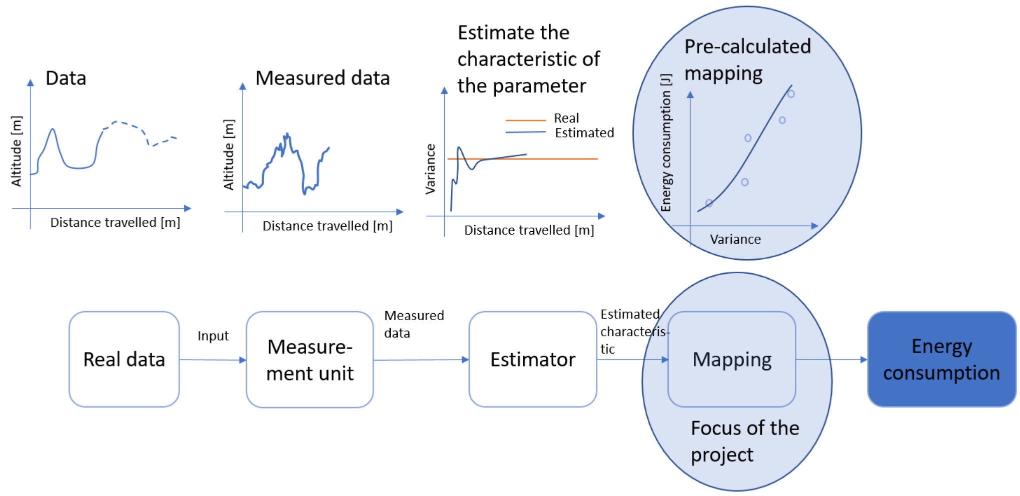

Figure 2.5: At each new data point measured, a new value for a parameter characteristic is estimated based on the accumulated data and the old values. The energy consumption is then found in the pre-calculated mapping system.

Before implementing the application described above, simulated data rather than real data will be used as the first step to try the method, see figure 2.6. It is easier to begin with the simulated data since it is simplified and accessible without a measurement unit system being implemented.

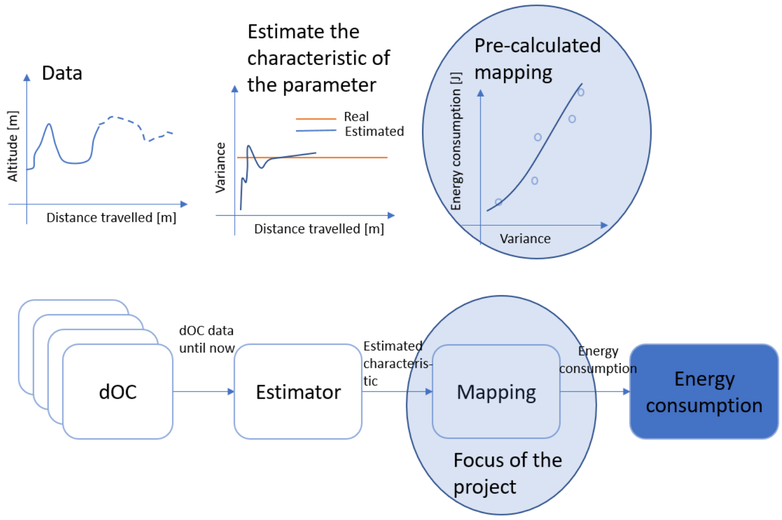

Figure 2.6: Similar to the live situation but uses simulated data. At each incoming data point, a new variance is estimated based on the accumulated data and the old variances. The energy consumption is found in the pre-calculated mapping system.

3
Environment models and estimation

In this chapter, the parameter models will be described thoroughly to understand how to create new dOCs. It will also outline how the total energy consumption is calculated and give an example of how to estimate the variance.

3.1 Investigated parameter models

Three parameters were decided upon since they have a major impact on the energy consumption for the vehicle, these were the topography, curvature and speed bumps. All parameters discussed within this section comes from Pettersson's report [10].

There are also other parameters for the road, weather and traffic category which have a significant impact on vehicles energy consumption. Including more parameters would naturally increase the quality of the estimation but the computational power required would also drastically increase as stated previously. Therefore, starting with a few parameters to try the approach was the first step.

3.1.1 Topography

The topography is described as an altitude for a given position, or as the road grade, which is the percentage change between two altitude values. The small segments between each altitude value, or the sampling frequency, is defined as L_s which was set lower than the total length of the road. To be able to generate the topography, road slope with an autoregressive model was used. Where the slope $Y_k \in R$ is a random variable for each part, k [10]. The autoregressive model then looks as follows:

$$Y_k = aY_{k-1} + e_k, \quad e_k \sim \mathcal{N}(0, \sigma_e^2), \tag{3.1}$$

where the parameter σ_e is the amplitude error and a is the autoregression coefficient.

The variance of the topography amplitude was derived from (3.1):

$$\sigma_Y^2 = \frac{\sigma_e^2}{1 - a^2} \tag{3.2}$$

σ_Y is the standard deviation of the road slope and σ_Y^2 is the variance of it. The greater it is set, the more frequent a steep road slope showed up in the road, which in turn means a more hilly profile for the road. Converting the road slope to altitude (z_k) was necessary due to the topography in the dOC format being described as altitude.

$$z_{k+1} = z_k + \frac{y_k}{100} L_s \tag{3.3}$$

The altitude is a graph composed of straight segments of lines and is called a piecewise linear function. Due to the piecewise constant function Y_k, the results were mirrored to get an even comparison.

One way to choose the standard deviation, σ_Y, for the topography was to follow the global transport application system (GTA) constructed by Volvo Trucks. The system is used in the COVER project and was created to find the most optimal specification of the vehicle for the customer. σ_Y was divided in flat, predominantly flat, hilly and very hilly, the values are shown in 3.4. [1]

$$\begin{aligned} \sigma_Y &< 1.29 && \text{Flat} \\ 1.29 \leq \sigma_Y &< 2.58 && \text{Predominantly flat} \\ 2.58 \leq \sigma_Y &< 3.87 && \text{Hilly} \\ 3.87 \leq \sigma_Y & && \text{Very hilly} \end{aligned} \tag{3.4}$$

The chosen σ_Y's were within these intervals.

3.1.2 Curvature

Curvature is defined as the shape of a road on the horizontal plane. Each curve can be seen as an isolated event, as it was done in [10]. The parameters to describe the curves were the location, curvature and curve segment length with the notations X, C and L_c respectively. Modelling each of them with a statistical approach gave the curvature characteristics of the road.

The model for the location of the curves is given by a Poisson process. Meaning that when a curve occurs, the probability of when the next curve appears is not changed.

$$X_{k+1} - X_k \sim \text{Exp}(\lambda_C), \tag{3.5}$$

Where λ_C is the intensity of how often the curves occur. The radius of a curve was modelled as follows,

$$R' = \frac{1}{C} - r_{turn}, \quad \ln R' \sim \mathcal{N}(\mu_C, \sigma_C), \tag{3.6}$$

Where R' is the shifted radius. The minimum road radius r_{turn} was set to 12m, for which real roads are designed. The shifted radius was modelled as a log-normal distribution with μ_C as the mean and σ_C as the deviation. The length of the curve was also modelled in the same way but with a different mean, μ_L, and deviation, σ_L.

$$\ln L_c \sim \mathcal{N}(\mu_l, \sigma_L), \tag{3.7}$$

From these statistical models, a great number of dOCs with curvature could be created and tested in a simulation environment, the powertrain represented in chapter 4. Limiting the scope, the studied curvature parameter characteristics were only μ_C and σ_C, while the other characteristics were held constant. This way the estimated energy consumption for the curvature could be mapped with the variances and the mean values in a three dimensional way.

The GTA system in [1] did not included any values for the curvature, hence why the variances and the mean values were chosen as used in [10]. Here it was divided in 9 cases as can be seen in table 3.1.

Table 3.1: Table with value for all characteristics describing curvature

	Case 1	2	3	4	5	6	7	8	9
σ_C	0.82	0.90	0.98	1.02	1.10	1.18	1.22	1.30	1.38
μ_C	0.50	1.50	2.50	3.10	3.75	4.40	4.60	5.25	5.90
λ_C	3	3	3	3	3	3	3	3	3
μ_L	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2	3.2
σ_L	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1

To limit the scope of the project two of the five parameter characteristics were chosen as mentioned previously. The first is the curve radius log-mean, μ_C, which modifies how much the road bends. The second is the variance of the curve radius, σ_C.

3.1.3 Speed bumps

Constructing the speed bumps parameter model consisted of modelling the mean number of speed bump occurrences happening within a certain distance. The intensity of speed bump occurrences was set as an input to generating the dOCs. The intensity, λ_b, is Poisson distributed and gives the position of when the occurrences happen.

$$X_{k+1} - X_K \backsim \text{Exp}(\lambda_b) \tag{3.8}$$

The event of a speed bump leads to a reduced velocity of the vehicle. The speed reduction depends on the height (S_h), length (S_l) and angle (S_α) of the speed bump. For this model, the simplification of setting the height and length constant was made. The value for the height of the speed bump was set to $S_h = 0.15$m and the value for the length was set to $S_l = 1$m.

For every speed bump, the minimum and maximum velocity, v_{min} and v_{max} were randomly assigned within a closed interval. The angle S_α for every speed bump could then be calculated based on the assumption that a higher velocity over the speed bump should be coupled with a lower angle and vice versa.

$$S_\alpha = (v_{max} + v_{min}) - v \tag{3.9}$$

The intensity values (λ_b) were uniformly distributed, as can be seen in Table 3.2. The interval limits were chosen like that of the curvature.

Table 3.2: Speed bump parameter characteristics settings describing speed bumps for 9 different intensity values.

	Case 1	2	3	4	5	6	7	8	9
λ_b	0.10	0.34	0.58	0.81	1.05	1.29	1.53	1.76	2.00
v_{min}, v_{max}	10,20	10,20	10,20	10,20	10,20	10,20	10,20	10,20	10,20

3.2 Parameter model connection

The method to combine all parameter models' influence on the energy consumption was done by assuming that each parameters model do not interact with each other, that they can be regarded as independent. This means that if one parameters model is removed or changed, the other parameters models energy consumption does not get affected. When evaluating how much each parameter model is affecting the energy consumption, all other parameter influences needs to be removed. To do this the parameter models not being investigated are in the dOC format set to zero or their default non-interference value, E.g 20°C for the temperature. Setting the influences to zero can for example mean setting the curvature of the road to be a straight road if only the topography is to be investigated. It can also represent flattening the topography which means no hills will appear or removing all speed bumps.

A simulation case of a dOC in VehProp always runs with a road that is either straight or curved. In other words, a simulation can not run if, for example, the topography is the only parameter model which is active. Meaning that some base conditions must be met. The energy consumption from the basic case is called E_0, or E_C if curvature exists for the case being investigated. When the HEV is advancing along the road, it is subjected to forces induced by aerodynamic and rolling resistance. These forces increase the energy consumption and are always included in the basic case. The other parameters models are called E_Z and E_B which are the energy consumption estimations from the topography and speed bumps respectively.

To summarize, to extract the energy contribution from only a specific parameter model, it is necessary to remove the energy consumption estimate from the basic case.

Equation (3.10) shows how all energy consumption are added up to the total energy consumption, E_{tot}.

$$E_{tot} = E_0 + E_z + E_C + E_b \tag{3.10}$$

3.3 Characteristics estimation

The parameter characteristics are not always the same and therefore estimation of such can be different for each characteristic. For example, the topography was chosen to have one characteristic which is the variance of the road slope while the curvature parameter was chosen to have two characteristics and these were the mean of the curve and the variance of it. All chosen characteristics, variance, mean value and intensity, can be estimated with the proposed algorithm below.

Since the unknown route is considered, new data is measured at each distance travelled. Meaning that the characteristics have to be estimated and updated each time new data comes in. A forgetting factor is a good way to put less importance on the old data when the characteristics of new incoming data has changed. This factor weighs the importance of low wrong adjustment and a fast convergence rate [11]. The algorithm proposed in report [12] will be used to handle the requirement of updating the characteristics estimation. The weighting terms $\sum_{i=1}^{k} W_i$, will be interpreted as $\frac{1-\alpha^{k+1}}{1-\alpha}$, and the algorithm is as follows,

$$\begin{aligned}
M_1 &= X_1 \\
M_k &= M_{k-1} + \frac{\alpha^k}{(\frac{1-\alpha^{k+1}}{1-\alpha})}(X_k - M_{k-1}) \qquad \text{,where k = 2, ...,n} \\
\bar{X} &= M_n \\
T_1 &= 0 \\
T_k &= T_{k-1} + \frac{\alpha^k}{(\frac{1-\alpha^{k+1}}{1-\alpha})}(X_k - M_{k-1})(X_k - M_{k-1})\frac{1-\alpha^k}{1-\alpha} \\
S^2 &= \frac{T_n}{\frac{n-1}{n}\frac{1-\alpha^{k+1}}{1-\alpha}}
\end{aligned} \tag{3.11}$$

Here, the M and $\bar{X}$ are the mean value, α is the forgetting factor, S^2 is the variance. Mean value estimation is included in the algorithm and therefore intensity, which is $\frac{1}{M}$, is included as well.

4
Electric Powertrain Model

In the coming sections VehProp, the OC system, variance estimation and energy consumption estimation will be explained. For a further and deeper explanation about VehProp and the OC system the reader is referred to report [13]. The purpose of having a working powertrain model is to produce results through simulation. The model is a central part to create the relation between OC parameters and energy consumption. The accuracy of the powertrain model to simulate real HEV behaviour is also important for the shapes of the relations between the OC parameters and the energy consumption.

4.1 Fully electric powertrain model

The developed electric powertrain model is included in the vehicle model in VehProp. The VehProp environment was developed in MATLAB and Simulink and uses statistical models to create scenarios of the surrounding vehicle environments, such as road conditions, weather, and traffic, to simulate the vehicle dynamics.

The electric powertrain used in the project was based on Iuri Barros's [2] hybrid powertrain for long haul trucks. The hybrid powertrain has an ICE as the main propulsion source, the model also has an electrified dolly which includes all parts of an electric powertrain. The involved systems were the pedal, control, propulsion, braking, transmission, vehicle chassis and battery.

Barros's powertrain is a hybrid powertrain and it is rather straightforward to transform the model into a fully electric powertrain model. This is done by removing the ICE parts of the model and making necessary changes to upscale the electric part to be used as the main power source. After transforming the hybrid powertrain into an electric powertrain, it was possible to extract the energy consumption from the battery when testing with different values on the parameter characteristics for the parameter models.

By reducing Barros's hybrid powertrain [2] the electric powertrain in figure A.1 was obtained, which is placed in the appendix chapter. The control system in the hybrid powertrain was found to be intertwined and complicated for this project. Instead, a new control system was developed, see figure 4.1.

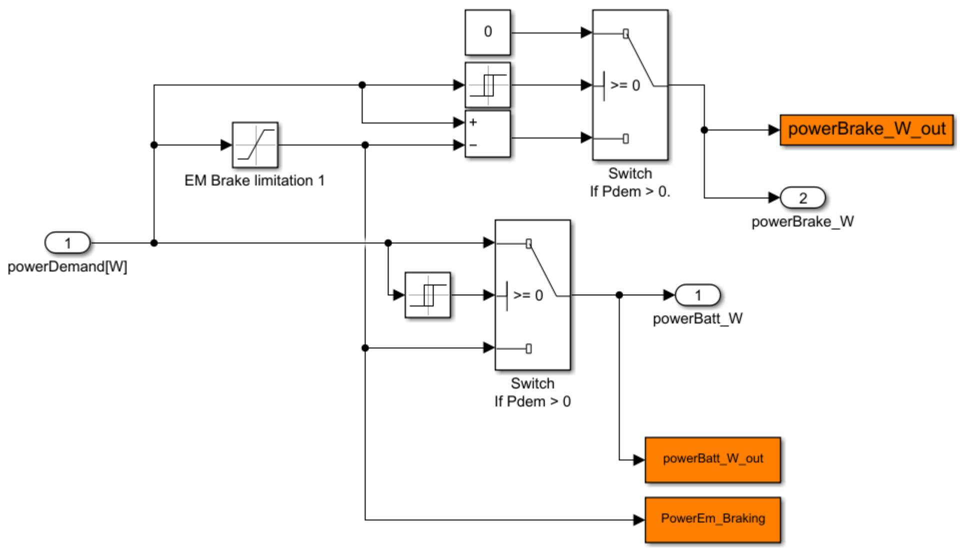

Figure 4.1: The power demand is divided between the battery and disc brake. When power demand shifts from positive to negative the battery shifts to regenerate. If the negative power demand exceeds the regenerative brake limitation, the disc brake supplies the extra brake power required.

The point of the control system is to divide the power demand into disc brakes, propulsion and regenerative brakes. When the power demand is positive or zero, such as when the system wants to drive forward, all power demand goes to the propulsion. This can be seen in the switch lower down in the figure 4.1.

A negative power demand is obtained when the system (vehicle) is braking, this causes the switches to go over to the brake system. The regenerative brakes have a limitation implemented that only allows for values from zero to the largest negative power, which the battery can regenerate. If the power demand is less than the amount of power the regenerative brakes can handle, then the braking power will only be generated through the regenerative brakes. But if it is larger, the disc brakes will complement it with its braking power, see figure 4.2.

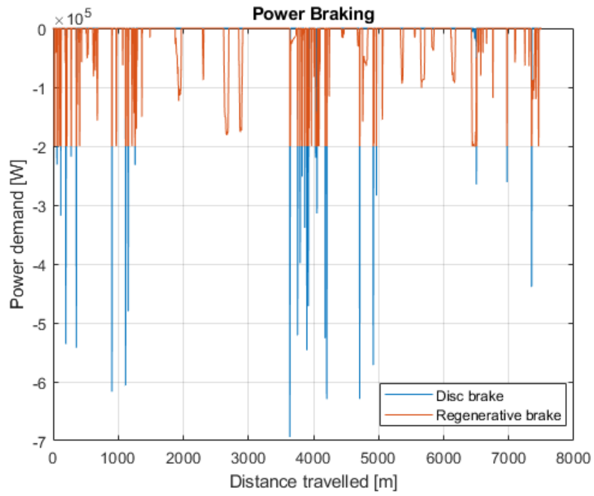

Figure 4.2: When the braking exceeds the regenerative capacity (set to $2 \cdot 10^5$W), the disc brake complements it with its braking power

Looking at the state of charge plot, see figure 4.3, the battery level goes down over time as expected. For some occurrences, the battery level increases slightly. This is a sign of the regenerative brakes working as intended, recharging the battery as the breaking action is enforced.

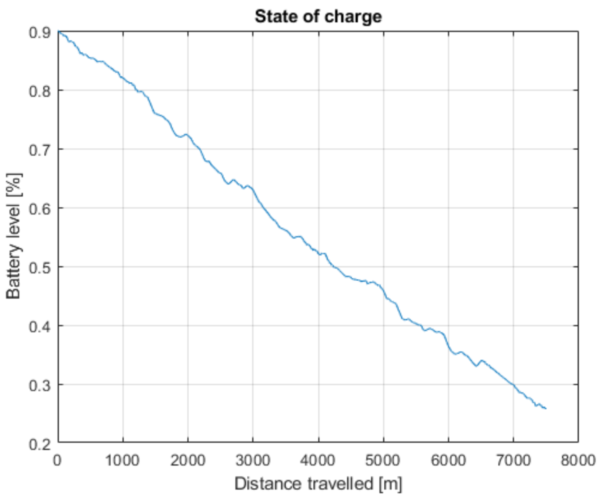

Figure 4.3: Battery level in the HEV decreases at every distance travelled except when the regenerative brake is applied.

The value at the end of the cycle is the energy consumption throughout the complete dOC, as shown in figure 4.4.

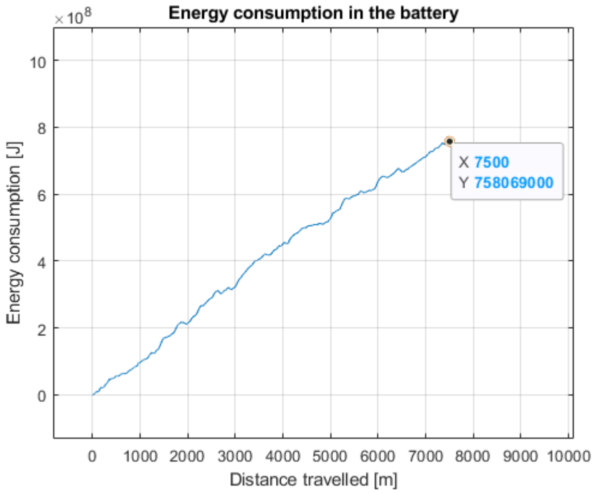

Figure 4.4: Energy consumption changes throughout the travelled distance. The endpoint of the line is the total energy consumption accumulated throughout the road.

When the OC format only has a straight road and all other parameters are set to zero, the energy consumption for a vehicular mass of 20 tons results in $E_0 = 6.7067 \cdot 10^8$J, likewise a mass of 40 tons results in $E_0 = 9.1 \cdot 10^8$J.

4.2 Vehicle properties

When running the generated dOCs in the HEV powertrain model the results are heavily dependent on what underlying properties the HEV system has. These properties are the electric motor, battery and road friction. The values are displayed in table 4.1. Other general information about the vehicle is displayed there as well. The modelling of the HEV is important since the results of the simulation will depend on the model used.

Table 4.1: Vehicle properties

Heavy electric vehicle (HEV)	
Vehicle properties	Settings (case 1 & 2)
Nr. electric motors	{2, 4}
Electric motor power max	18500 [W]
Electric motor power min	-18500 [W]
Motor efficiency	90%
State of charge max	90%
State of charge min	20%
Assumed road friction	0.9 [-]
Wheel radius	0.49 [m]
Vehicle mass	{20, 40} [ton]
Rolling resistance coefficient	0.0056 [-]

The model for the major energy consumers for the vehicle such as the aerodynamic and rolling resistance can be viewed in figure 4.5.

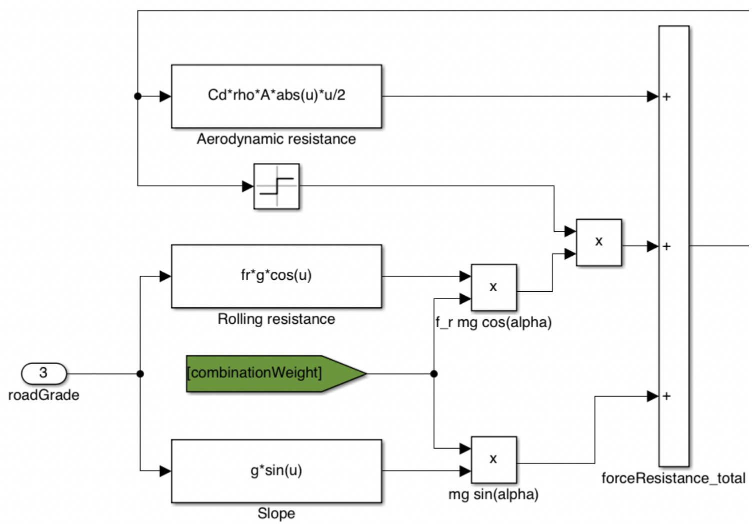

Figure 4.5: Aerodynamic and rolling resistance model

5

Simulation

The main topic of this chapter is to present the results and simulations. This chapter covers the relationship between the parameter characteristics and energy consumption for each parameter model and how doubling the mass of the vehicle affects this relation. Also the results for the recursive variance estimation is displayed.

5.1 Topography

How to extract the energy consumption is shown in figure 4.4. Doing this for 100 dOCs for each chosen value for the investigated variances gave 900 data points. By taking the mean value for each of the 100 dOCs, the result became as shown in figure 5.1.

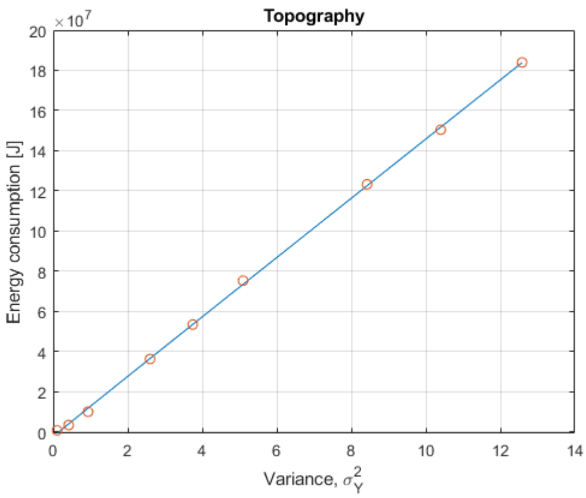

Figure 5.1: Result for how the variances are connected with the mean estimated energy consumption.

Figure 5.1 shows how the energy consumption changed with values of the variances. With an increased variance, the expected energy consumption increased as well. To use the result as a mapping, some sort of interpolation or function fitting was required. In this project a function fitting method was used, polyfit in Matlab, the function became, $E_Z = 10^7 \cdot [1.4628(\sigma_Y^2)^2 + 0.0596\sigma_Y^2 - 0.2329]$.

- What happens when the mass is doubled for the HEV? To demonstrate this, an HEV with 40 tons was simulated for the same 900 dOCs as it was done for the original 20 ton HEV, the results were then compared. The logarithmic relation between the energy consumption and the variance resulted in figure 5.2. To give an illustration of the difference in percentage, the right graph was plotted for each variance. Note that the difference in energy consumption in percentage was around 150% when the mass was doubled.

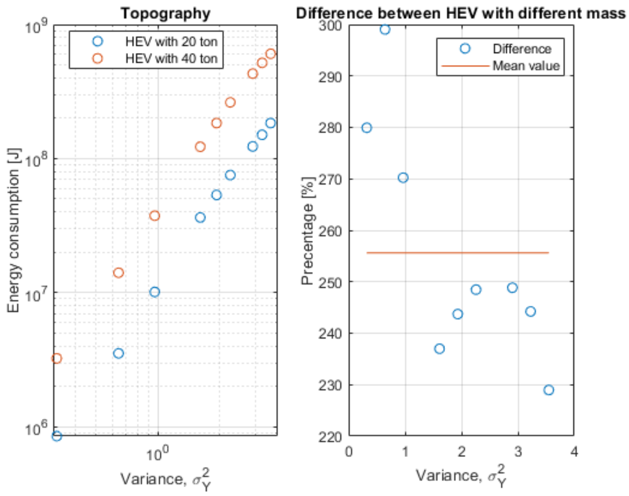

Figure 5.2: The result for how the variances were connected with the estimated energy consumption in a logarithmic scale and the percentage differences.

The same test was done in figure 5.3, but this time without the regenerative brake. The results showed that when doubling the mass, the increase of energy consumption was only around 50%. Meaning a drop of 100 percentage points of energy consumption when the regenerative brake was removed.

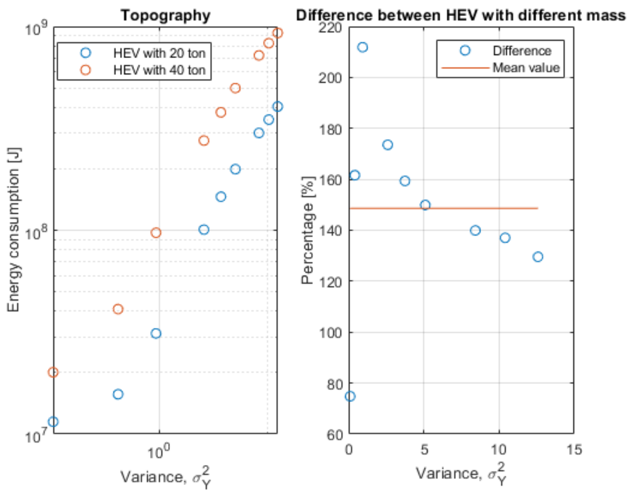

Figure 5.3: The result for how the variances were connected with the estimated energy consumption in a logarithmic scale and the percentage differences without the regenerative brake.

5.2 Curvature

Two parameter characteristics varied for curvature and these were the mean value of the curvature, μ_C, and the variance of it, σ_C^2. Similar to the previous parameter model, there were 9 selected μ_C and 9 σ_C^2. Simulating 100 dOCs for for each μ_C and σ_C^2 generated a matrix of size $9 \times 9 \times 100$, which resulted in 8900 dOCs.

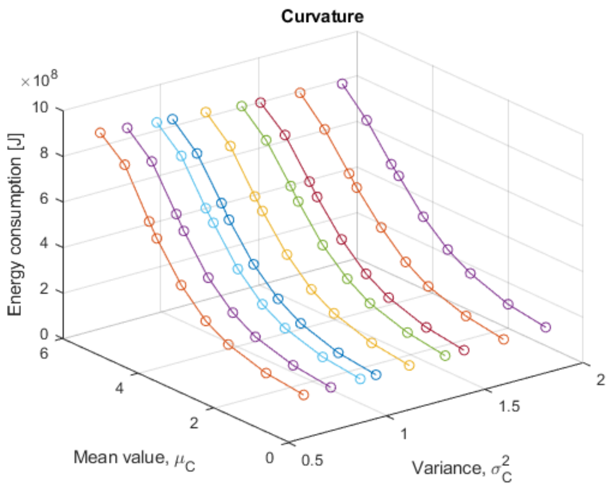

Figure 5.4: The result for how the variances and mean values were connected with the estimated energy consumption.

From figure 5.4 the observation can be made that μ_C has a larger impact on the energy consumption than σ_C^2. If σ_C^2 has the value of 0.82 which is the first selected value of the variance, then the energy consumption increases with, $E_C = 10^8 \cdot [0.311(\mu_C)^2 - 0.534\mu_C + 1.484]$. To find the correct value a look-up table would have been suitable.

5.3 Speed bumps

The parameter characteristics for the speed bump that varied were the intensity and the angle. The intensity is shown on the x-axis in figure 5.5. Again, as shown in figure 5.5, when the intensity increased the energy consumption increased linearly. Using the polyfit tool in Matlab gave the function, $E_b = [3.0323 \cdot 10^{10} \cdot \lambda_b - 4.6253 \cdot 10^5]$.

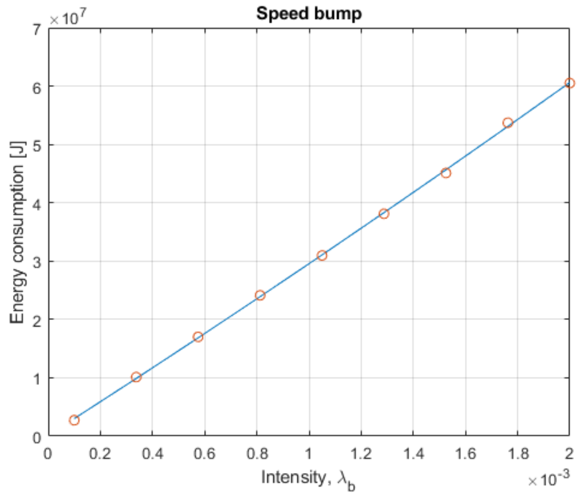

Figure 5.5: The result for how the intensities were connected with the estimated energy consumption

Doubling the mass of the HEV, as done for the topography, was tested for the speed bumps parameter model as well. The logarithmic plot on the left side of figure 5.6 demonstrates how the different masses relate to each other. In addition, the right plot shows the differences in percentage. Meaning that when doubling the mass, the energy consumption did not double but got only an increase of around 50%.

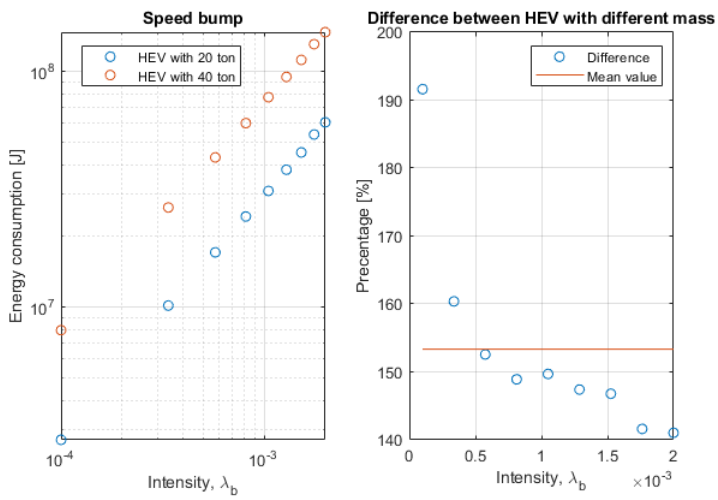

Figure 5.6: The result for how the intensities were connected with the estimated energy consumption in logarithmic scale and the percentage differences.

The same test was done in figure 5.7 but this time without the regenerative brake. The result showed an increase of energy consumption of around 5% when the mass was doubled.

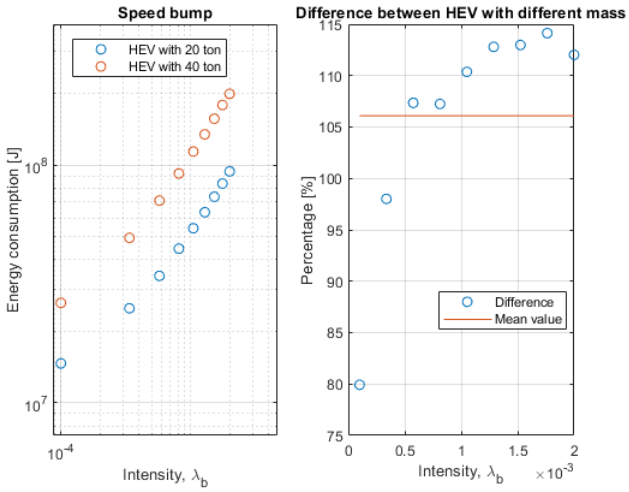

Figure 5.7: The result for how the intensities were connected with the estimated energy consumption in logarithmic scale and the percentage differences.

5.4 Variance estimation

To test the provided model for the variance estimation with a forgetting factor, derived in (3.11), a dOC with a standard deviation (σ_Y) of 0.3225 was used. The variance then becomes the square of it, $\sigma_Y^2 = 0.104$. As seen in figure 5.8, the estimated variance found the real variance fast, just after 100 samples. However, the variance does not converge fully even after 6202 samples. Note that there were 6202 samples in total for the topography.

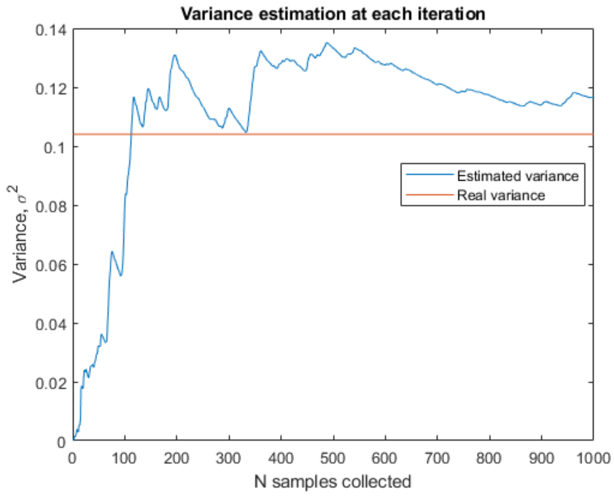

Figure 5.8: Behaviour of how the variance estimator performed against real variance

The mean value estimator shows similar behaviour as variance. The estimator comes near conversion after 500 samples.

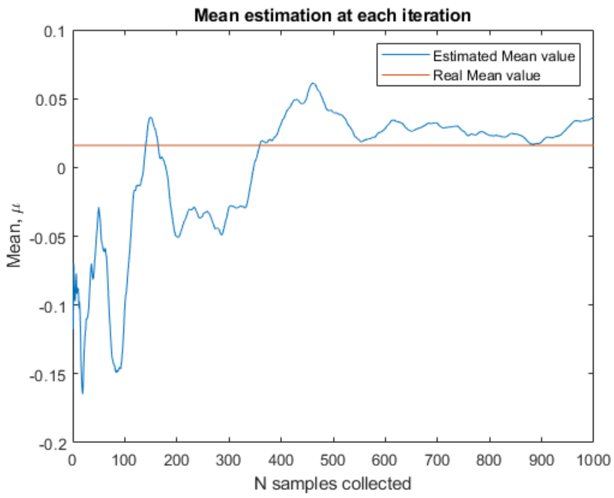

Figure 5.9: Behaviour of how the mean value estimator performed against real mean value

6
Discussion & conclusion

6.1 Discussion

Looking back at the research questions stated in the introduction.

- How can the models in the OC format be used to make an energy consumption prediction for heavy electric vehicles in cases of unknown routes?
- How do different environmental factors affect the energy consumption of the vehicle?

The process of making the energy consumption prediction as stated in the first question is through the mapping between the characteristics of the considered parameters to the energy consumption. The mapping itself is a look-up table which allows for a fast prediction rather than a bunch of heavy calculations which would have been needed to be performed if the mapping was not created. The connection between parameter characteristics energy consumption is estimated based on a large number of simulated scenarios generated by the models shown in chapter 3. The next suggested step would be to more extensively verify how well the summed energy consumption from all considered parameters relates to the real simulated energy consumption, this would be a way to assess the performance of the constructed estimator.

The second question addresses the result of the project. For the topography, the relation between the slope variance of the road and the energy consumption displays a linear behavior. This means that as the slope variance increases more energy will be consumed. A similar conclusion can be made for the speed bumps, the relation between the intensity of a speed bump occurring and the energy consumption related to that was also found to be linear. However, for the mean value of the curve, the increase in energy consumption for curvature displayed different increasing behavior and the value variance of the curve shows low impact on the energy consumption. How much all the investigated parameters energy consumption should theoretically increase is hard to know without a verification method and without inputs from the real world to compare against, which future work could focus on. The only tests done in the project was on the behaviour of the powertrain model which is described in the next paragraph. The main tests were on how the mass the affected the energy consumption and also the effect of the regenerative brakes.

When the mass of the HEV was doubled for the topography model, the energy consumption did not double but instead gave an increase of more than 150%. Why it was not 100% is hard to pinpoint due to the complexity of the OC format and VehProp. However, the HEV had a regenerative braking system that was set to a limitation of regenerating 200kW regardless of the mass. Taking this into account, the control system in the HEV used the disc brakes when the braking power demand was greater than 200kW, which happens more frequently if the mass is higher. Thus the reason for the 150% increase is likely due to more energy transferring to heat rather than to regenerative energy. This was why another test without a regenerative brake was conducted. The result was just around 50% for that test, why it dropped by 100% from 150%, was also not completely clear.

A similar test was done but this time for the speed bump model. The first test resulted in a 50% increase in energy consumption when the mass doubled. By removing the regenerative brakes, the energy consumption was only increased by 5% when the mass doubled. Why it displays such a small increase in energy consumption is still hard to determine.

The next step in finding the relations was to estimate the characteristics of the parameters to map them to the corresponding energy consumption. For the estimation of the variance and mean value, there was a suggestion on how to perform it in (3.11), and in section 3.3 it shows promising results where the estimated variance and mean value converged near the real value. More than this has not been done in this project and the suggestion for future work for this area is described in section 6.3.

The project was primarily based on the research previously conducted by the COVER project but the approach to use some sort of mapping or cluster in an online case was originally derived from [8]. The authors used two different parameters, one was the speed of the vehicle and the other was the power usage. The average error energy consumption compared to the "real" energy consumption used resulted in a 10% difference. The proposed approach in this project has not yet been verified and thus can not be compared to the previous literature. This project does however provide meaningful results by providing a method on how to perform the relation mapping between the characteristics of the parameters and the energy consumption. Another benefit of the method presented is that before adding up all of the energy consumption estimates for the individual parameters, they all have an inherent value in that they could provide the driver with a suggestion on how to best adjust the vehicle for different parameter characteristics for maximum energy efficiency.

- "Why were unknown routes even considered as done in the mentioned report and this project? One could say that the route is already known before driving, especially for heavy trucks. Meaning all parameters are known with historical data." This is not always the case, some parameter models are hard to predict throughout the route because of the ever-changing environment and its uncertainty. Examples of parameters with high uncertainty are wind speed and road conditions. The aim of this project was not to compete against what was already done but to complement it. The results of the cases with unknown routes could complement the known route at special events, such an example could be road works or sports events that were not considered when the energy consumption was estimated for the known routes. In the cases of unknown routes when such a thing happens on the road, it may indirectly detect such a special event. A more frequent stop or slow down of the HEV corresponds to a higher intensity which in turn could be mapped to corresponding energy consumption. This method could be used at special events as mentioned or as historical data for constructing the case of the known route. The suggested method has not been done but there are possibilities to implement it in the future.

6.2 Conclusion

In summary of the result, the energy consumption increases with the characteristics of the parameters topography, curvature and speed bumps. The last part for estimating the characteristic is not done yet and future work within this area has to be made before assessing the performance of the approach. In conclusion, although it is easier to estimate the energy consumption in a predetermined and known route, there are parameters that are hard to determine beforehand. This is why the project for the unknown route proceeded. But to only use this method for the unknown route could give unnecessary errors since more often than seldom, the route for an HEV is pre-planned and the majority of parameters that make up the surroundings of the vehicle can be determined beforehand. Combining approaches for the known and unknown routes can therefore complement each other's drawbacks, which creates a reliable online case approach.

6.3 Future work

There is already some future work mentioned in the discussion but this chapter will focus completely on what future work could be done. This is especially important since the verification process for the approach of the unknown routes remains to be implemented.

As mentioned in the discussion, the verification of the estimation of the parameter characteristic has not been fully implemented and there is room for improvement. There are two main challenges that need to be overcome in order to complete the estimation verification. The first one is to get a conversion to the real variance, see figure 5.8, such as to get an example where the conversion is relatively good. A suggestion is to dive deeper into the method and check if it is possible to fully converge. The second achievement is to enable the variance estimation even if the real variance changes, for example when the altitude goes from flat to very hilly then the variance estimator results should reflect that changing behavior. The same goes for when evaluating for the estimation of the mean value.

The last step of the energy consumption prediction is the mapping which is described in section 2.2.2. Performing the mapping and then calculating the error has yet to be made to evaluate whether or not the approach performed well. As for now, dOCs can be used to perform the evaluation. This simplifies the reality. Further work should include real measured data.

There are other steps to improve the approach which is recommended to do after finishing the above:

- Include more parameter models in weather, road and traffic if possible.
- Include more characteristics in the already used parameters. In the parameter model curvature, only two out of five characteristics describing the curvature were used. For the topography, the hill length, L_h was constant in this project but is, in reality, a varying parameter that depends on the ever-changing slope angle. This is described in [10]. For the speed bumps model, only the intensity and angle of such an event was varied in the parameter model.
- There is also room for improvement in the powertrain model for the HEV. For example, the battery model is based on an integral method that accumulates errors every step. [2]. Improving the battery model would reflect the real world better.

Lastly, for those who are interested, here are some ideas to investigate which the authors of this report did not manage to within the scope of this project.

- Instead of using for example the slope variance of a data set to determine how hilly the road is, could there be other ways to determine how hilly a road is? Maybe one could look at the features of the road such as counting how often steep slopes appear instead?
- The mass of a passenger car is often held constant throughout a trip while a heavy vehicle changes it mass more often. How is the energy consumption affected for such an application which could be the case for busses or delivery trucks.
- One of the big energy consumers of a heavy vehicle is the rolling resistance. The conditions on the ground are hard to determine which means the energy consumption of it is hard to estimate. Are there other ways to tackle this problem?

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A
Appendix 1

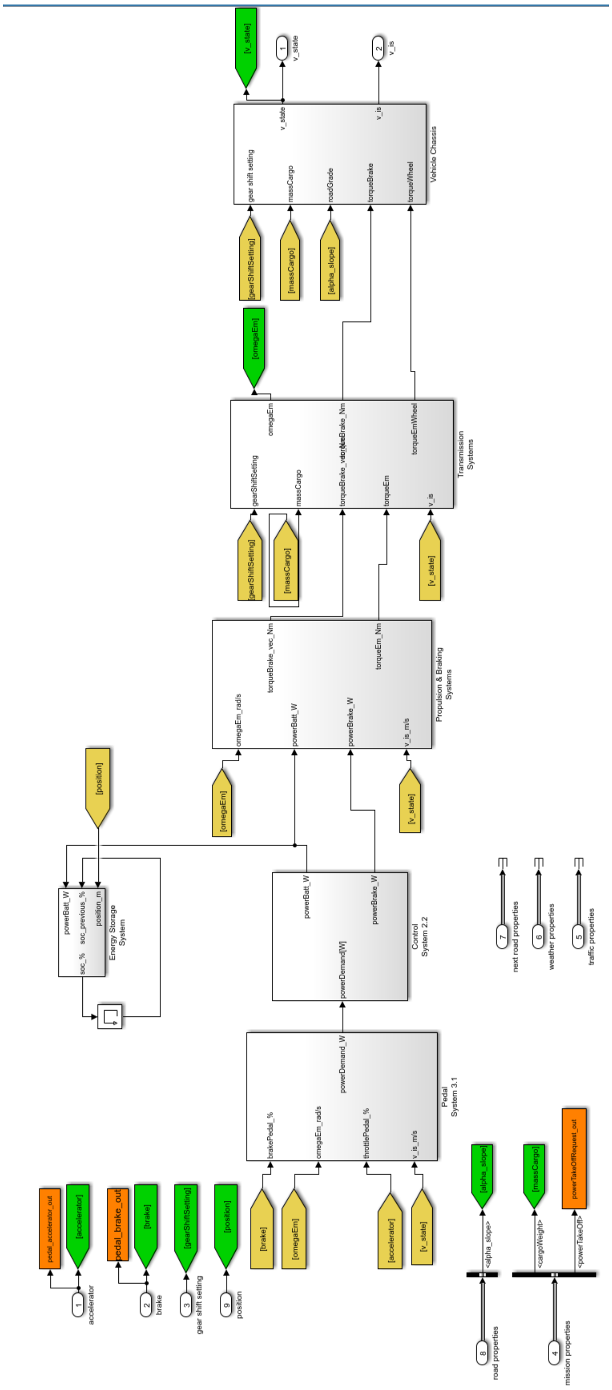

Figure A.1: Overview of the result when reducing Barros's hybrid powertrain [2] to a the electric powertrain

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